

## Supplementary Material:

# Discovery of a Recursive Principle: An Artificial Grammar Investigation of Human Learning of a Counting Recursion Language

Pyeong Whan Cho\*, Emily Szkudlarek and Whitney Tabor

\*Correspondence: Pyeong Whan Cho: pcho4@jhu.edu

#### 1 EXPERIMENTAL SEQUENCES

To save space, each experimental sequence is presented as a sequence of sentences rather than a sequence of words:  $S_1 = 1 \ 2 \ 3 \ 4$ ;  $S_2 = 1 \ 1 \ 2 \ 3 \ 4 \ 2 \ 3 \ 4$ ;  $S_2^* = 1 \ 1 \ 4 \ 3 \ 2 \ 4 \ 2 \ 3$ ;  $S_3 = 1 \ 1 \ 1 \ 2 \ 3 \ 4 \ 2 \ 3 \$ 

Sequence 1 (Experiment 1)

 $S_1 \ S_1 \ S_1 \ S_1 \ S_1 \ S_1 \ S_1 \ S_2 \ S_2 \ S_2 \ S_2 \ S_1 \ S_2 \ S_1 \ S_2 \ S_1 \ S_2 \ S_1 \ S_2 \ S_2 \ S_1 \ S_2 \ S_1 \ S_2 \ S_2$ 

Sequence 2 (Experiment 1)

Sequence 2 was the same as Sequence 1 except that  $S_2$  was replaced with  $S_2^*$ .

Sequence 3 (Experiment 2)

 $S_1 \, S_1 \, S_2 \, S_1 \, S_2 \, S_1 \, S_1 \, S_1 \, S_2 \, S_1 \, S_1 \, S_1 \, S_2 \, S_1 \, S_2 \, S_1 \, S_2 \, S_1 \, S_2 \, S_1 \, S_3 \, S_1 \, S_1 \, S_2 \, S_1 \, S_3 \, S_1 \, S_2 \, S_3 \, S_1 \, S_2 \, S_3 \, S_3 \, S_1 \, S_2 \, S_3 \, S_3$ 

### 2 GRAMMAR BEARING POINT LANGUAGE CLASSIFICATION ALGORITHM

We consider a model profile of trial-level prediction accuracy, FiniteM, for a level-N sentence which is well described by a finite-state grammar  $G_M$  consisting of M rules that generate  $S_1, \dots, S_M$ . An individual with  $G_M$  behaves as follows: First, she always predicts 2 after 1 given the instruction and the nature of feedback; although we describe her prediction responding to word 1, the following algorithm ignores the prediction accuracy on those nondeterministic transitions so this arbitrary choice does not influence the algorithm's product. Second, she treats a subsequence of symbols in level-N sentence which matches a level-M sentence (M < N) as a level-M sentence. Third, she predicts 1 after 4 occuring after the subsequence. For example, consider an individual who has knowledge of level-1 sentence but does not have knowledge of level-2 sentence. The individual is assumed to treat the subsequence of 1 2 3 4 nested in a Level-2 sentence [1 [1 2 3 4] 2 3 4] as if it was an actual level-1 sentence. Then, the individual would predict 1 after the first 4 because a new sentence is expected after a level-1 sentence. This is a wrong prediction. After a wrong prediction is made, the individual takes the strategy to predict 1 when

encountering the next 4's until she encounters 1 which indicates the beginning of a new sentence. This individual's prediction accuracy profile would be (0,1,1,1,0,1,1,1) and this profile for  $S_2$  would be classified into Finite1. See Table 2 in the main article for other profiles under consideration.

Let Seq be a sequence of sentences. Seq is initially set to the experimental sequence but it will be updated by removing its first sentence, Seq(1), during running this algorithm. Let Lv be the level of Seq(1); Lv would be 1 if Seq(1) is the sentence without embedding (i.e.,  $S_1$ ). Let AnsLv be the level of the response to Seq(1). By the response to Seq(1), we mean a vector of binary prediction accuracy for all *deterministic* transitions of Seq(1). If the response vector is the same as a model profile FiniteN, AnsLv is set to N. If the response vector does not coincide with any FiniteN vector, AnsLv is set to 0. For example, the response vector to level-2 sentence might be (1,0,1,1,1,1) from (1,0,1,0,1,1,1,1) with prediction accuracy of nondeterministic transitions as boldface. No FiniteN vector equals this response vector. In this case, AnsLv would be 0. Let GH (SentNo) be a grammar underlying an individual response pattern estimated after the individual processed the SentNo-th sentence in a sequence; GH corresponds to an individual's grammar trajectory over the course of learning. The following algorithm takes a sequence of trial-level prediction accuracy data and returns a sequence of grammars. The grammar classification algorithm is presented below:

- 1. Create a vector of length 0 Resp in which the n-th element represents AnsLv to the most recent level-n sentence so far. Set SentNo and FlagFirst to 0.
- 2. Increase SentNo by 1. Check if Seq(1) is the first instance of level-Lv sentence where Lv indicates a level of embedding of the sentence. If so, increase the length of Resp by 1 and set a variable FlagFirst to 1. In other words, the length of Resp increases whenever the algorithm encounters a novel sentence type.
- 3. Check Anslv for the current Seq (1) and replace the Lv-th element of Resp with Anslv. In Steps 2 and 3, it is assumed that the first instance of level-Lv sentence occurs after the first instances of the sentence types with lower levels  $(1, 2, \dots, Lv-1)$  of embedding.
- 4. If any element of Resp is 0, set GH (SentNo) to 0 which does not correspond to any symbolic grammar under consideration.
- 5. If no element of Resp is 0, find the maximum k such that Resp (1) = 1, ..., Resp (k) = k, where k should be equal to or less than the length of Resp. It suggests that the individual correctly recognized level-k and all the lower level sentences. If k equals the length of Resp (suggesting that the individual correctly predicted all deterministic transitions of the most recent instances of all sentence types) and FlagFirst equals 1 (suggesting that the individual correctly processed all deterministic transitions of the first instance of a novel sentence type), set GH (SentNo) to 5 which corresponds to the target recursive grammar  $G_R$ . In all the other cases, set GH (SentNo) to k which corresponds to a finite-state grammar  $G_k$ .
- 6. Set FlagFirst to 0; update Seq by removing Seq (1) from it; if Seq is null/empty, then terminate; otherwise, go to 2.

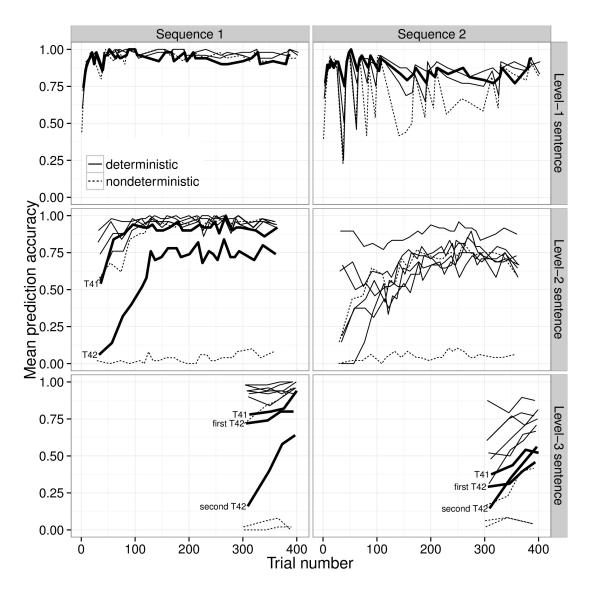
For example, if an individual had processed the sentences  $\cdots$   $S_2^{19}$   $S_1^{20}$   $S_1^{21}$   $S_1^{22}$   $S_3^{23}$  where the superscripts indicate the sentence indices in the experimental sequence (and the subscripts indicate the embedding level as before), the individual's grammar after processing  $S_3^{23}$  was decided based on the prediction accuracy profile on three sentences  $S_1^{22}$ ,  $S_2^{19}$ , and  $S_3^{23}$ ; by that sentence, no  $S_4$  had been presented so the accuracy profile on  $S_4$  was not considered at that time. Let us assume that the prediction accuracy profile was as follows: 1 1 1 1 for  $S_1^{22}$ , 0 0 1 1 1 1 1 1 for  $S_2^{19}$ , and 0 1 0 1 1 1 1 1 0 1 1 1 for  $S_3^{23}$ . According to Table 2 in

the main article, the profile can be described as Finite1 for  $S_1$ , Finite2 for  $S_2$ , and Finite2 for  $S_3$ . Because the individual correctly responded to  $S_1$  and  $S_2$ , and showed the prediction accuracy profile for  $S_3$  that corresponds to having knowledge of  $S_2$ , but not of a deeper level, the individual's grammar is classified as  $G_2 = \{S \rightarrow 1\ 2\ 3\ 4,\ S \rightarrow 1\ 1\ 2\ 3\ 4\ 2\ 3\ 4\}$ . Note that we use FiniteN to refer to a sentence-level profile of prediction accuracy motivated by symbolic rules and use  $G_N$  to refer to a bearing point grammar underlying the vector of prediction accuracy profiles, in this case, (Finite1, Finite2, Finite2).

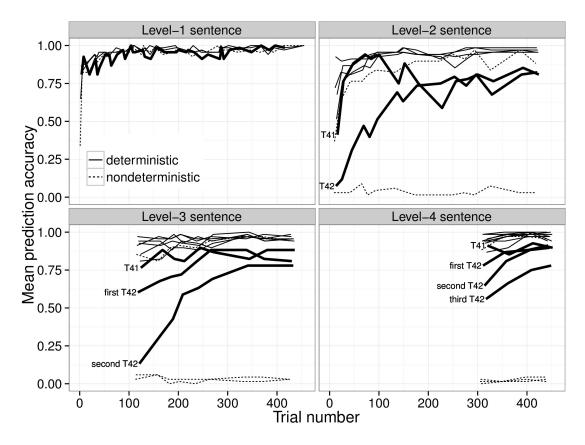
Consider another case where the prediction accuracy profile for  $S_3^{23}$  is 0 1 0 1 1 1 1 1 1 1 1 1 1 1 while the other profiles are the same as in the previous example. In this case, the profile is consistent with Finite3 for  $S_3$  so the vector of prediction accuracy profiles is (Finite1, Finite2, Finite3). If the  $S_3$  under consideration is the first instance of  $S_3$ , the grammar is taken to be  $G_R$  based on the participant's successful spontaneous generalization. On the other hand, if the  $S_3$  under consideration is not the first instance of  $S_3$  and the participant's profile of prediction accuracy for the first instance of  $S_3$  was not classified into Finite3, the grammar is taken to be  $G_3$  consisting of three rules:  $S \to 1 \ 2 \ 3 \ 4 \ 2 \ 3 \ 4 \ 2 \ 3 \ 4$  and  $S \to 1 \ 1 \ 2 \ 3 \ 4 \ 2 \ 3 \ 4$ , and  $S \to 1 \ 1 \ 2 \ 3 \ 4 \ 2 \ 3 \ 4$  because there is no evidence of generalization beyond experience.

#### 3 SUPPLEMENTARY FIGURES

Frontiers 3



**Supplementary Figure 1.** Trial-level mean prediction accuracy in Experiment 1. The dashed and solid lines present the average prediction accuracies on nondeterministic ( $T_{11}$  and  $T_{12}$ ) and deterministic transitions in each sentence type. The thick lines present the average prediction accuracies on  $T_{41}$  and  $T_{42}$ . Recall that different level-2 sentences ( $S_2$  and  $S_2^*$ ) were used in Sequence 1 and 2. There were no  $T_{41}$  and  $T_{42}$  in the level-2 sentence ( $S_2^*$ ) used in Sequence 2.



**Supplementary Figure 2.** Trial-level mean prediction accuracy in Experiment 2. The dashed and solid lines present the average prediction accuracies on nondeterministic  $(T_{11} \text{ and } T_{12})$  and deterministic transitions in each sentence type. The thick lines present the average prediction accuracies on the critical deterministic transitions  $(T_{41} \text{ and } T_{42})$  in each sentence type.

Frontiers 5